Prediction of Tides Using Neural Networks at Karwar, West Coast of India

Rakshith Shetty*1, Dwarakish G. S.2

Department of Applied Mechanics and Hydraulics, National Institute of Technology Karnataka, Surathkal Srinivasnagar P.O., Mangalore, Dakshina Kannada-575 025, Karnataka, India

*1shr.11ms20f@nitk.edu.in; 2dwaraki.gs@gmail.com

Abstract

Tidal level is an indispensable record that is required for the safe navigation of ships in harbours; planning and safe execution of various coastal engineering projects. Harmonic analysis, the most widely used method for prediction of tides, involves the computation of harmonic constants which require excessive data. Numerical models require large amount of data in the form of bathymetry and boundary conditions. Artificial Neural Network (ANN) has been widely applied in coastal engineering field, since last two decades in variety of problems related to time series forecasting of waves and tides, prediction of sea-bed liquefaction and scour depth, and estimation of design parameters of coastal engineering structures. Its ability to learn highly complex interrelationship based on provided data sets with the help of a learning algorithm along with built in error tolerance and less amount of data requirement, making it a powerful modelling tool in the research community. Study has been carried out to predict tide levels using Feed-Forward Back Propagation (FFBP) network with Levenberg-Marquardt (LM) algorithm. Field data of Karwar tide gauge station has been used to train and test the network performance. Effect of network architecture on the performance of model also has been studied. Results are compared with those of predictions carried out using Auto Regressive Integrated Moving Average (ARIMA) technique. ANN provides better prediction when compared to ARIMA. It can be concluded that ANN can be used to predict tides at Karwar successfully using short term hourly tide level data.

Keywords

Artificial Neural Networks; Tide; Prediction; Feed Forward Back Propagation; Karwar

Introduction

Tidal level plays a major role in various activities like planning of harbour, determination of Mean Sea Level (MSL) and navigation depth, drawing marine boundaries, storm surge monitoring and even in disposal of sediments. Monitoring and prediction of tidal level, is thus important for the smooth planning and execution of its related activities. Tidal ranges are largely affected by the gravitational pull of Sun and Moon on the oceanic water body, the component of tide called 'the astronomical tide'. Other factors like bottom topography, sea-level pressure, and wind speed also contribute to the tidal range called 'non-astronomical tide'. Traditional method of prediction of tides is done by Harmonic method, which accounts for the parameters or constituents of astronomical tide. It is given by the eqn.

$$H = H_0 + A\cos(at+\alpha) + B\cos(bt+\beta) + C\cos(ct+\gamma) + \ldots \quad (1)$$

where, H is the height of the tide at location, H_0 is the MSL, A, B, C are the amplitudes of the constituents and $(at+\alpha)$ are the phases of the constituents. Once the harmonic constituents or constants are found out for a location by means of least mean squares (Doodson, 1928) or Kalman Filtering as used by Yen et al (1996), it can be used to predict the tides by reuniting them with the available astronomical relations prevailing at the time for which predictions have to be done. For a detailed account of Harmonic analysis and prediction of tides one can refer to (Schureman, 1971). The major drawback of this method is the large amount of continuous tide data that is required to determine the tidal constituents (Reid, 1990). As well the method does not take in to consideration the various hydrodynamic and meteorological parameters. Though Kalman filtering requires fewer amounts of data, its prediction is for short-term duration. Numerical models like finite difference method require accurate boundary conditions and geometric information (Chen et al, 2007). Although including more number of constituents in the harmonic analysis improves the accuracy it leads to problem of growing memory and calculation time. In addition, harmonic analysis and Kalman filtering methods are ineffective in supplementing the lost tide data, especially when tidal level changes are complex in nature and data available is incomplete (Liang et al, 2008). Further harmonic analysis is restricted to the prediction of the tides at a particular station only as tidal constituents vary from one place to another.

Artificial Neural Networks have been applied in the

field of coastal engineering to overcome the major drawback of excessive data requirement of existing methods, ever since Mase et al (1995) used it for stability analysis of rubble mound breakwaters. Later Tsai and Lee (1999) used Back Propagation Network (BPN) along with gradient descent method to predict tides at Taichung harbour and Mirtuor coast. It was revealed from the study that long duration predictions can be done using very small duration data set. The requirement of determining harmonic constant was overlooked in this method as prediction was made based on the models trained with past tidal records. In a similar study conducted to check the applicability of ANN where different tide conditions exist (diurnal, semi-diurnal and, mixed) by Lee and Jeng (2002) at three different stations, satisfactory results were obtained at all the stations. Lee et al (2002) and Lee (2004) showed that ANN can be used to supplement missing data. The study also made use of BPN with no hidden layers to finalise the major tidal constituents of the location out of 69 tidal constituents. Study showed that two months of tidal records were required to get clear results, whereas, by using one months' data, one can get an idea on the type of tide existing at a location. Yearly tide level data is required for the same purpose if constituents were to be found out by means of traditional harmonic analysis method. In a comparative study conducted on hydrodynamic and ANN models at two different stations, the hydrodynamic model outperformed ANN in terms of CC value (Vivekanandan and Singh, 2002). Though the results were marginally (order of 0.020) in favour of hydrodynamic models, hydrodynamic models required initial boundary conditions as input. The study concluded that ANN can be used as a substitute for hydrodynamic models considering the sparse data requirement and less computational time taken. Regional neural network water level (RNN-WL) prediction model developed to predict sea water level at a station using data obtained from other stations in the region, provides a cost effective way to obtain long-term tidal data for regional stations where the established tide observation gauges are expensive and instead can be relocated to other new sites (Huang et al., 2003).

In a study (Rajasekaran et al., 2006) in which functional neural networks (FNN) and sequential learning neural networks (SLNN) were applied to predict tide levels, the FNN was found to be more accurate, which uses domain knowledge rather than data knowledge used by conventional ANN, that is to say, FNN learn functions as opposed to learning of weights by ANN. On the other hand, SLNN involves large number of iterations of the order 140,000 but takes less computational time mainly because of the presence of a single neuron in the hidden layer. Seven parameters affecting the tide generating forces from tide theory were used as input to create Tide Generating Force-Neural Network(TGF-NN) by Chang and Lin (2006). The model was trained using one year tidal data and same data was used to find harmonic constants in harmonic method consisting of 60 constituents HM (60). The results showed that TGF-NN is as powerful as HM (60) when one year tidal data is used and with 2 hour lead time. The model was compared with other tide prediction models like NAO.99b, HM (26) harmonic analysis with 26 constituents and Response-Orthotide (R-O) method and the results showed TGF-NN outperforming all the other models.

Chen et al., (2007) combined ANN and wavelet analyses to extend the predictions for 5 year duration and to improve the prediction quality, and formed various models for locations in and around Taiwan and South China Sea. Makarynska and Makarynskyy (2008) used feed forward neural network with Resilient Back Propagation (RBP) learning algorithm to predict tide levels. The RBP learning algorithm provided quicker computation. They also modelled a network to fill in missing data using 12h prior and after data as inputs and residual value between interpolated and observed tide levels as the output targets. The results obtained were satisfactory with CC value between 0.93-0.96 using various lengths of tide data as input. In a recent study conducted by Filippo et al.,(2012) at two stations in Brazil, the effect of meteorological parameters of wind speed and sea level atmospheric pressure on tidal predictions were studied by incorporating 3 hour wind speed data and atmospheric pressure data in the input along with calculated tide data from harmonic analysis method. One year tide data was used for training. The importance of the meteorological parameters were highlighted by the results obtained which showed a considerable decrease in error from 26% to 12% and from 31% to 2% in case of station 1 and station 2 respectively where studies were undertaken.

Method

Artificial Neural Networks (ANN)

Development of ANN can be attributed to the attempt carried out to mimic the working pattern of human

brain. Its success lies in its ability to exploit the non-linear relationship between input and output data by continuously adapting itself to the information provided to it, by means of some learning process. ANN can be classified based on network type into feed forward and feedback or recurrent networks. The basic difference between the two is that, in feed forward networks, the information is passed from one layer to the other in a forward manner till the output is obtained in the output layer. Whereas in, feedback network, the output obtained in the output layer is fed back in to the network through input layer thus this type of network will have a minimum of single loop in its structure. Further, ANN can also be classified based on learning type i.e. supervised and unsupervised learning. In supervised learning, a set of data input and corresponding output is fed into the network and the calculated output is compared with target output (given output values to the network), and the difference between the two is the error and through various error correction measures available, the network adapts itself till the error reaches a minimum value or fixed number of iterations is complete. In unsupervised learning, the networks are tuned to statistical regularities of the input data by learning rules like radial basis function and others, here no input-output data set is presented to the network.

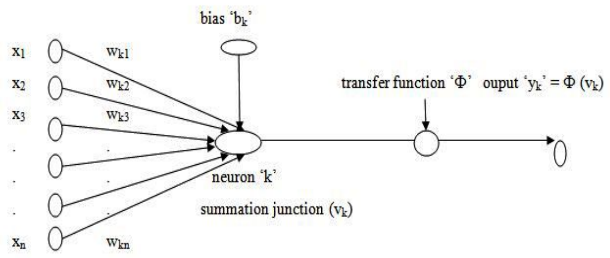

FIG. 1 BASIC MODEL OF ANN

Fig. 1 shows the basic mathematical model of ANN where, $x_1, x_2, x_3 \ldots x_n$ are the input parameters; $w_{k1}, w_{k2}, w_{k3} \ldots w_{ki}$ are the weights associated with the connections i.e. synaptic weight connections from input neuron 'i' to neuron 'k' and i = 1 to n. 'k' neuron is the summing junction where net input is given by,

$$u_k = \sum_{i=1}^{n} wki * xi \tag{2}$$

and,

$$v_k = u_k + b_k \tag{3}$$

where b_k is the bias value at the k^{th} node. The final output y_k is the transformed weighted sum of v_k or in other words y_k is the function of v_k represented by,

$$y_k = \Phi(v_k) \tag{4}$$

where Φ- is the transfer function used to convert the summed input. A non-linear sigmoid function, which is monotonically increasing and continuously differentiable, is the commonly adopted transfer function. It is mathematically expressed as,

$$y_k = \Phi(v_k) = 1/[1+\exp(-avk)] \tag{5}$$

Others such as hardlim, logsig, tansig and prelim can also be used to get the desired result.

The most commonly used learning algorithm in coastal engineering application is the gradient descent algorithm, in which the global error calculated is propagated backward to the input layer through weight connections, during which the weights are updated in the direction of steepest descent or in the direction opposite to gradient descent. However, the overall objective of any learning algorithm is to reduce the global error, E defined as

$$E = \frac{1}{p}\sum_{p=1}^{p} Ep \tag{6}$$

and,

$$E_p = \frac{1}{2}\sum_{k=1}^{N}(ok - tk)^2 \tag{7}$$

where E_p is the error at the p^{th} training pattern, O_k is the obtained output from network at the k^{th} output node and t_k is the target output k^{th} output node and N is the total number of output nodes. Levenberg-Marquardt algorithm (Levenberg, 1944; Marquardt, 1963) used in this study can be written as

$$W_{new} = W_{old} - [J^T J + \gamma I]^{-1} J^T E\,(W_{old}) \tag{8}$$

where J is the Jacobien of the error function (E), I is the identity matrix and γ is the parameter used to define the iteration step value (Panizzo and Briganti, 2007; Gunaydin, 2008). It minimizes the error function while trying to keep the step between old weight configuration (W_{old}) and new updated one (W_{new}) small.

The performance of the network is measured in terms of various performance functions like sum squared error (SSE), mean squared error (MSE), root mean squared error (RMSE) and Co-efficient of Correlation (CC or 'r') between the predicted and the observed values of the quantities. Lower value of RMSE and higher value of CC indicate better performance of the network.

The major drawback of the Feed Forward Back Propagation (FFBP) is that of the network getting trapped in the local minima. The over learning phenomena due to high learning late may lead to oscillatory behaviour of the network. Very large

number of neurons in the hidden layer will lead to complex learning and might take large number of iterations to terminate the process. Less number of input data makes it difficult for the network to learn all the relationship involved between the input and target parameters. Too many variations in the involved data set also will diminish the accuracy of the network. The mentioned setbacks can, however, be overcome by selecting the optimum architecture of the network using various techniques like sensitivity analysis to select most effective input parameters and reduce network size to decrease the computational time required. Using generalization techniques to improve the quality of the input data like Principal Component Analysis (PCA) will also help in improving prediction quality. Other ANN models based on conjugate gradient algorithm, radial basis function, cascade correlation algorithm and recurrent neural networks can be used to overcome this (ASCE Task Committee, 2000). Recently, many studies have been carried out combining ANN with statistical and other Artificial Intelligence (AI) methods of Genetic Programming (GP) and Fuzzy Logic (FL) systems to improve the forecasting accuracy and duration as well.

The non-linear data driven self-adaptive approach, opposed to the high data requirement of the numerical models along with requirements of initial boundary and geometry of the study area in case of ocean engineering application, makes ANN attractive and a powerful tool for modelling when underlying data relationship is unknown. Many studies have shown that once the network is validated for a particular task they can be successfully applied for practical on field applications as well (Londhe and Panchang, 2006). The detailed account of theory and mathematics basics behind ANN can be found in literature of (Haykin, 2006).

Auto Regressive Integrated Moving Average (ARIMA)

The general Auto Regressive Moving Average (ARMA) model introduced by Box and Jenkins (1976) includes autoregressive as well as moving average parameters, and explicitly includes differencing in the formulation of the model. Specifically, the three types of parameters in the model are the autoregressive parameters (p), the number of differencing passes (d), and moving average parameters (q). The parameters are estimated so that the sum of squared residuals is minimized. The estimates of the parameters are used in the forecasting to calculate new values of the series and confidence intervals for those predicted values. The estimation process is performed on transformed (differenced) data; hence, before the forecasts are generated, the series be integrated so that the forecasts are expressed in values compatible with the input data. This automatic integration feature is represented by the letter I in the name of the methodology (ARIMA = Auto-Regressive Integrated Moving Average).

The ARMA model, proposed by Box and Jenkins (1970) with the idea of linear filter to estimate the stochastic data is defined by the equation:

$$x_y = \phi_1 x_{t-1} + \phi_2 x_{t-2} .. + \phi_p x_{t-p} + \xi_t - \varphi_1 \xi_{t-1} - \varphi_2 \xi_{t-2} .. - \varphi_q \xi_{t-q} \quad (9)$$

in which p and q are separately the order of the autoregressive and moving average model, x_t and x_{t-1} are the observation at the time instant t and t- i, ξ_t and ξ_{t-i} are the residual values and, ϕ_1 to ϕ_p and ξ_1 to ξ_q are the finite set of weighted parameters. For the ARMA model, larger amounts of the measured data will provide a better prediction. Furthermore, longer computational time for the parameter identification is required. Also, the parameters involved in ARMA will be affected by the changes of some environmental or sociological variables.

Materials

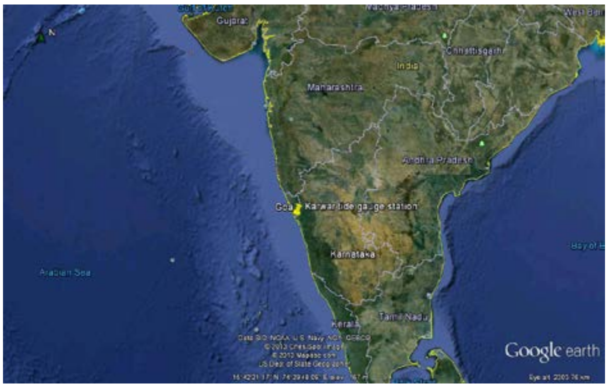

FIG. 2 LOCATION OF STUDY AREA

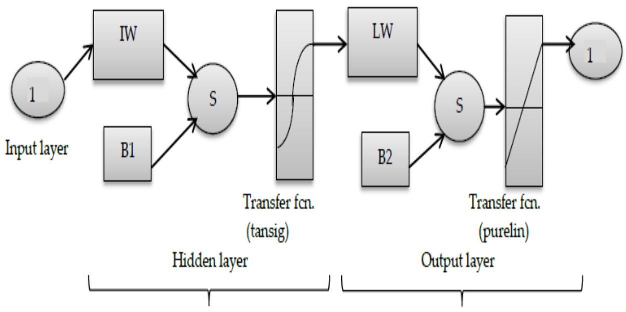

FIG. 3 THE ANN STRUCTURE FOR ONE MONTH PREDICTION USING ONE MONTH DATA, HAVING SINGLE INPUT AND OUTPUT LAYER NODES.

Three years of hourly gauge measured tide level data from December 2008 to December 2011 of Karwar

station (14°48.183′N 74°06.865′E), obtained from National Institute of Oceanography, Goa was utilized in the study. Predictions were carried out for varying length of duration using a week's data, month's data and one year' data as input. Three layered FFBP network with an input layer, hidden layer and output layer were used with Levenberg-Marquardt (LM) algorithm for the purpose of prediction of tide. Tangent-Sigmoid (tansig) and linear (purelin) transfer function were used in hidden and output layer respectively. The data was normalised to fall in range of -1 to 1 to speed up the learning process. One thousand epochs were set as the stopping criteria of training process of network for all the predictions undertaken.

Results and Discussion

The four weeks' prediction was carried out using one weeks' hourly data from 1/1/2009 to 7/1/2009 as input. The target data set comprised readings of four weeks duration from 8/1/2009 to 4/2/2009 (28 days), a week's data having 168 time steps represent a single node in this case, similarly output layer consists of four nodes for four weeks of data. Subsequent weeks in similar fashion were given as input and target for testing the trained network. The 'r' values showed marginal increase in 4 weeks' prediction which might be due to the increased number of target values available for the network generalisation. However, the 'r' value decreased for the 12 weeks' tide level prediction as one week' input data's range was too narrow to predict a long duration of 12week's tide level. The number of neurons was increased in hidden layer by one after every prediction. The best performance was obtained at six and two neurons in hidden layer during 4 weeks and 12 weeks prediction of tide levels. The training performance showed considerable increase in 'r' values but testing 'r' values drastically reduced hinting at the overfitting behaviour of the network when the number of neurons was increased beyond six and two during 4 weeks and 12 weeks tide level prediction when the number of neurons in hidden layer was increased. This phenomenon refers to a state where there is large number of neurons in hidden layer increasing the complexity of the network, but there is no significant amount of patterns to be learnt by the network based on given input-target datasets. As well in both the cases the prediction duration is large (4 weeks and 12 weeks) compared to input data of one week. Naturally, the range of targets will be greater than that of input provided, weakening the prediction capability of the network when new data set is fed to the network.

TABLE 1 MEAN SQUARE ERROR ('MSE') AND COEFFICIENT OF CORRELATION ('R') VALUES FOR TIDE LEVEL PREDICTIONS OF 4WEEKS AND 12 WEEKS.

Network structure	'mse'		'r'	
	Training	Testing	Training	Testing
1-6-4	1589.7	1656.1	0.625	0.579
1-2-12	1943.4	2461.5	0.463	0.299

Monthly prediction involved feeding the network with a months' data with 720 data points in a single input node. The year 2009 hourly tide levels data were divided in to twelve sets with 720 data points, each corresponding to 30 days of observation, hence the yearly data comprised 1/1/2009 to 26/12/2009(360 days). For one months' tide level prediction data from 1/1/2009 to 30/1/2009 and from 31/1/2009 to 1/3/2009 was given as input and target data respectively. The subsequent data of 30 days period were given as input and targets for testing purpose. The number of neurons was increased in the hidden layers, however, not much appreciable improvement was seen hence the number of neurons was taken as one for all the forthcoming predictions which has a month's data as input in a single node which involved one month data as input. Table 2 gives the results for monthly prediction duration of one month, two months and three months using one month input data.

TABLE 2 MEAN SQUARE ERROR ('MSE') AND COEFFICIENT OF CORRELATION ('R') VALUES FOR TIDE LEVEL PREDICTIONS OF ONE MONTH, TWO MONTHS AND THREE MONTHS.

Network structure	'mse'		'r'	
	Training	Testing	Training	Testing
1-1-1	331.77	529.50	0.928	0.884
1-1-2	735.54	917.36	0.830	0.802
1-1-3	1121.20	1142.0	0.728	0.716

Monthly prediction was carried out using first month of year 2009 as input and corresponding month of year 2010 as target, later first month of year 2010 input was taken as input and year 2011's corresponding month was given as target for training and testing purpose respectively. The results obtained were less satisfactory with 'r' value of 0.316 and 0.304 during training and testing of the network. This might be due to the time gap of 11 months between the input and target value.

Preliminary analysis done by taking monthly averaged values of the three years hourly data of tide levels showed that, from January till August, the average monthly tide level decreased and from September till January the levels showed rising trend during all the three years (Fig.4). Hence monthly

prediction was carried out based on this analysis dividing the data into two sets, one set consisting of tide levels of months from January till August and the other consisting of months from September till December of all three years. Predictions were carried out separately for each data set, and the data of year 2009 and 2010 were given as input and target for the training purpose and the tide levels of 2010 and 2011 was given as input and target for testing purpose of the network. Good results were obtained in case of data set one which comprised months from January to August and satisfactory results were obtained when September to December month's data was used for prediction. This decrease in prediction accuracy might be due to the fact that, in data set comprising the tide levels from January till August, there is a time gap of four months between input and target values whereas in the second case there is a time gap of eight months; as well the number of data points will be half as that is available in the first case for network generalisation. The optimum numbers of neurons were found to be ten for the first data set and five for the second which might be due to the greater number of input and output nodes (eight) in first case and just four in the second case. The results are tabulated in table3.

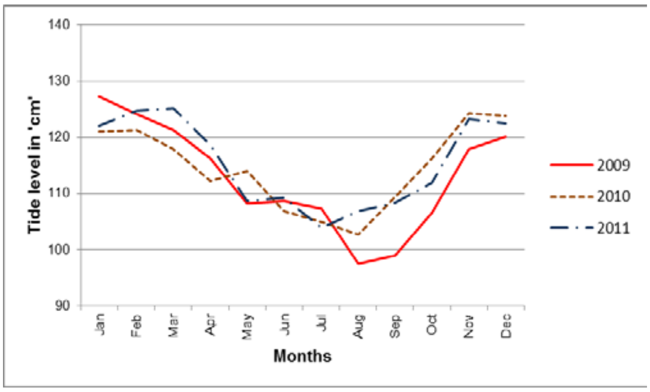

FIG. 4 PLOT OF MONTHLY AVERAGED TIDE LEVEL OF THE YEAR 2009, 2010 AND 2011.

TABLE 3 'MSE' AND 'R' VALUES FOR TIDE LEVEL PREDICTIONS OF 8 MONTH AND 4 MONTH DURATION USING INPUT AND OUTPUT DURATION OF SAME LENGTH AND MONTHS OF CONSECUTIVE YEARS.

Network structure	'mse'		'r'	
	Training	Testing	Training	Testing
8-10-8	613.50	1527.7	0.865	0.690
4-5-4	1587.0	1828.9	0.586	0.538

A year's hourly data set contains 8760 readings; however, this was cut short to 8640 and 8736 readings so that the data can be divided equally into 12 months composed of 30 days (720 readings) each and 52 weeks composed 7 days each (168 readings). Hence the first month will comprise data from 1/1/2011-30/1/2011, second month from 31/1/2011-1/3/2011 and so on till 26/12/2011.

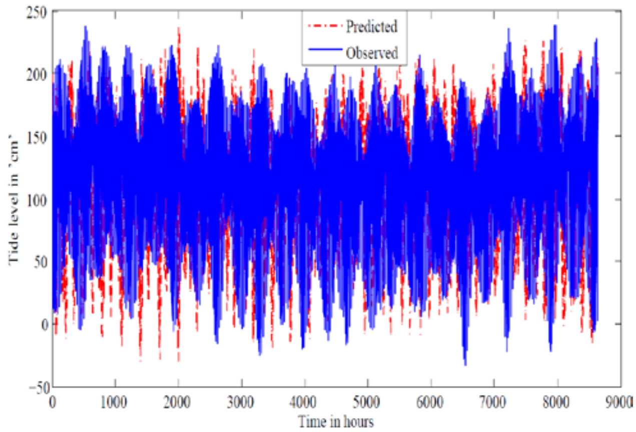

FIG. 5 GRAPH SHOWING THE PREDICTED AND OBSERVED HOURLY TIDE LEVEL VALUES FOR THE YEAR 2011 USING MONTHLY DATA SETS (1/1/2011-26/12/2011).

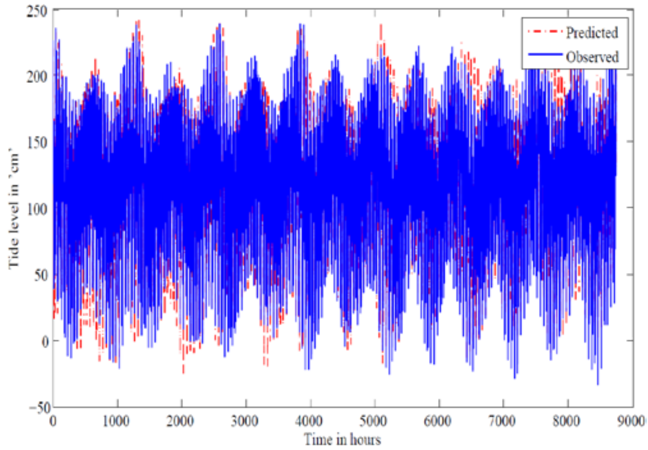

FIG. 6 GRAPH SHOWING THE PREDICTED AND OBSERVED HOURLY TIDE LEVEL VALUES FOR THE YEAR 2011 USING WEEKLY DATA SETS (1/1/2011-30/12/2011).

Prediction for entire year using 12 months data of year 2009 as input with equal number of input nodes was carried out giving the year 2010's tide levels of 12 months as target during the training process. The trained network was then used to predict the 2011's tide level using 2010 tide levels as the input. The results obtained were very good in this case and 'mse' value as low as 192.98 and 536.74 was obtained for training and testing respectively, also high 'r' value of 0.959 and 0.891 were obtained. The optimum number of neuron in hidden layer was found to be 10 in this case. The plot of observed values and predicted values is shown in the Fig.5. Figure 7 and Figure 8 give the scatter plot of training and testing of the network. Similarly year long predictions done using 52 weeks data of year 2009 as input and data of year 2010 as target in training process and next two consecutive years data as input and target for testing purpose, respectively, yielded very good results with training process 'r' value reaching up to 0.99 and testing 'r'

value reaching a value of 0.897. Once again the optimum number of neuron was found to be ten in this case as well. The 'mse' values were 14.13 and 478.47 for training and testing purpose respectively.

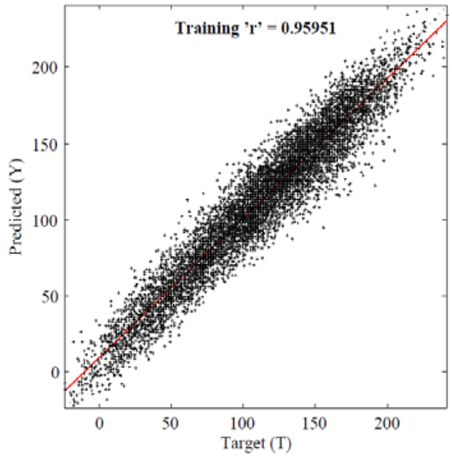

FIG. 7 SCATTER PLOT OF TRAINING OF NETWORK DURING YEARLY PREDICTIONS DONE USING MONTHLY DATA SETS

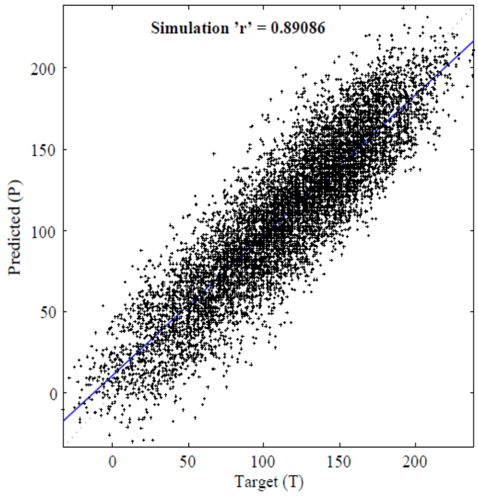

FIG. 8 SCATTER PLOT OF TESTING OF NETWORK DURING YEARLY PREDICTIONS DONE USING MONTHLY DATA SETS

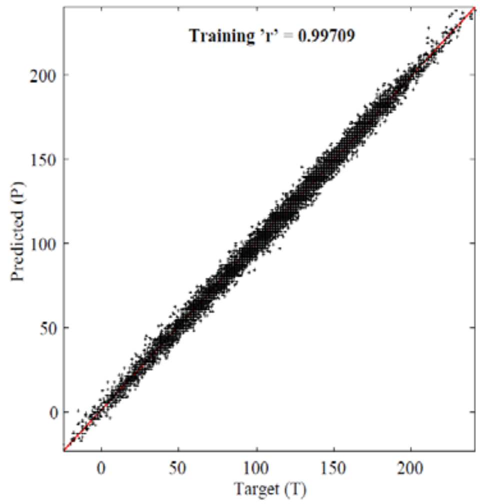

FIG. 9 SCATTER PLOT OF TRAINING OF NETWORK DURING YEARLY PREDICTIONS DONE USING WEEKLY DATA SETS

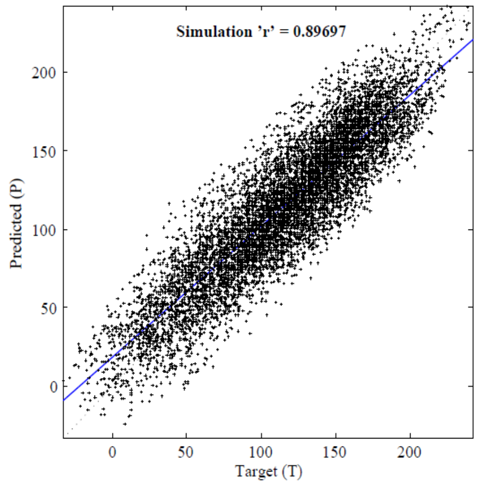

FIG. 10 SCATTER PLOT OF TESTING OF NETWORK DURING YEARLY PREDICTIONS DONE USING WEEKLY DATA SETS

TABLE 4 VARIATION OF 'MSE' AND 'R' VALUES WITH PHASE LAGS FOR TIDE LEVEL PREDICTIONS OF THE YEAR 2011 USING THE ARIMA MODEL.

Phase lag	'mse'	'r'
0	2290.87	0.237
1	2418.77	0.059
2	2206.09	0.303
3	1963.73	0.437
4	1961.43	0.438
5	2188.46	0.314
6	2401.20	0.106
7	2390.43	0.125
8	2193.99	0.311
9	2048.65	0.395
10	2130.75	0.350
11	2349.24	0.381
12	2146.80	0.071
13	2146.38	0.341
14	1672.81	0.558
15	1367.30	0.661
16	1507.30	0.615
17	1993.18	0.422
18	2391.70	0.119
19	2301.38	0.231
20	1696.62	0.548
21	1012.00	0.763
22	762.20	0.828
23	1133.60	0.730
24	1831.58	0.495

The results obtained from the ANN were compared with those of ARIMA model. In the ARIMA modeling, the data given for simulation purpose of ANN was used. Tide levels of the year 2010 were given as predictor series and 2011 as the series that had to be predicted. Mean squared error 'mse' and coefficient of correlation 'r' were taken as performance indicators to compare the results with those of ANN's. Predictions were carried out for time lags varying from one hour till 24 hours. The results of the same are presented in table 4. Best result was obtained for prediction done

with time lag of 22 hours with mse value of 762.201 and ‘r’ value of 0.828. The values were considerably less than those obtained by the ANN model (mse = 478.47 and r = 0.897) when predictions were carried out using yearlong weekly data sets.

Conclusions

ANN has been widely used in the field of coastal engineering for various applications. In this particular study, ANN has been used to predict hourly tide levels at Karwar station located on the west coast of India and the results have been compared with those of the standard ARIMA model. From the study carried out, the following conclusions can be drawn:

1. The results of the study were in good agreement with the previous studies that the larger the data set used for model training, better was the network created.
2. Too many neurons in the hidden layers will lead to overfitting of the network, causing poor predictions when new testing data sets are fed in to the network. Therefore, it is advisable to check the optimum number of neurons when new data sets with different number of input nodes and output nodes are fed.
3. Prediction of one month, two months and three months giving one month tide level as input has yielded good results with ‘r’ values greater than 0.9, 0.8 and 0.7 respectively. However, the result of monthly predictions by giving a months’ data of one year and same month’s tide level of next year as target value, yielded poor results as this introduced a time gap of 11 months between input and target data. The fact was evident when ‘r’ value increased for predictions carried out for four months from September till December giving similar month’s tide level data of previous year as input in the training of network, as time gap reduced to 8 months in this case and a further increase in ‘r’ value for predictions from January till August which reduced the time gap to four months.
4. Satisfactory results were obtained for a complete one year’s prediction based on previous year’s data which gave an ‘r’ value greater than 0.95 and 0.89 in both the cases when data was divided into monthly and weekly data sets for training and testing of the network respectively.
5. ANN outperformed the ARIMA model with 22 hour phase lag in terms of ‘mse’ and ‘r’ values justifying the application of the same for the purpose even without the phase lag correction.

The study showed that the ANN can be used for the prediction of tides successfully. However, for prediction with less data and data with large time gaps between them, studies can be undertaken using various advanced networks like dynamic network.

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Shetty Rakshith has completed his Post Graduation with Marine Stuctures as specialization from Department of Applied Mechanics and Hydraulics, National Institute of Technology Karnataka, Surathkal. He has published 4 technical papers in various national/international conferences/journals. His area of research is predictions of ocean parameters using artificial intelligence systems; Coastal and Ocean engineering.

Dr. G. S. Dwarakish is currently working as Professor in the Department of Applied Mechanics and Hydraulics, National Institute of Technology Karnataka, Surathkal, India. He had guided 5 Ph.D. scholars, 22 Master Degree Students for their dissertation and 08 batches of Under Graduate team projects. He has to his credit 100 plus technical papers in peer reviewed International and National journals and conferences. He is currently guiding 04 Ph.D. scholars, 03 M.Tech. students and 01 batch of UG students. He is also executing 02 R & D projects funded by national organizations. His areas of research include coastal engineering, sediment dynamics and applications of RS & GIS for coastal and water resources engineering.